Evaluating the Adequacy of Simulating Maximum and Minimum Daily Air Temperature with the Normal Distribution

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ABSTRACT

Weather simulation models are commonly used to generate synthetic daily weather for use in studies of crop growth, water quality, water availability, soil erosion, climate change, and so on. Synthetic weather sequences are needed if long-term measured data are not available, measured data contain missing records, collection of actual data is cost or time prohibitive, or when necessary to simulate impacts of future climate scenarios. Most weather generators are capable of producing one or more components of weather such as precipitation, temperature, solar radiation, humidity, and wind speed. This study focused on one generation component, the procedure commonly used by weather simulation models to generate daily maximum and minimum temperature. The normal distribution is used by most weather generators (including USCLIMATE, WXGEN, LARS-WG, CLIMGEN, and CLIGEN) to generate daily maximum and minimum temperature values. The objective of this study was to analyze the adequacy of generating temperature data from the normal distribution. To accomplish this objective, the assumption of normality in measured daily temperatures was evaluated by testing the hypothesis that daily minimum and maximum temperature are normally distributed for each month. In addition, synthetic temperature records generated with the normal distribution were compared with measured temperature records. Based on these analyses, it was determined that measured daily maximum and minimum temperature are generally not normally distributed in each month but often are slightly skewed, which contradicts the assumption of normality used by most weather generators. In addition, generating temperature from the normal distribution resulted in several physically improbable values.

1. Introduction

It is common to assume that daily maximum and minimum air temperature data are normally distributed, but in many cases the data are nonnormal (Grace and Curran 1993; Toth and Szentimrey 1990; Brooks and Carruthers 1953; Dumont and Boyce 1974). Deviations from normality occur when data are skewed, have relatively greater or smaller concentration near the mean (kurtosis), or have a relatively greater or smaller number of outliers (Helsel and Hirsch 1993; Haan 1977). The assumption of normality is important to most commonly used weather generation models, including USCLIMATE (Hanson et al. 1994), WXGEN (Williams 1995), LARS-WG (Semenov and Barrow 1997), CLIMGEN (Stockle and Nelson 1999), and CLIGEN (Nicks and Lane 1989), since these models use the normal distribution for simulating daily maximum and minimum temperature.

A fundamental analysis of the assumption of normality in daily maximum and minimum temperature is warranted because of the realization that this generally accepted assumption may not adequately represent measured temperature and because many efforts are under way to analyze and improve existing weather generation models and develop new ones (e.g., Johnson et al. 1996; Parlange and Katz 2000; Wilks 1999; Hayhoe 2000; Stockle and Nelson 1999; Johnson et al. 2000). Bruhn et al. (1980) evaluated the normality assumption on a limited dataset, but, to our knowledge, no detailed evaluation on the ability of the normal distribution to adequately represent measured daily maximum and minimum daily temperature across the United States has been conducted. Therefore, the objective of this study

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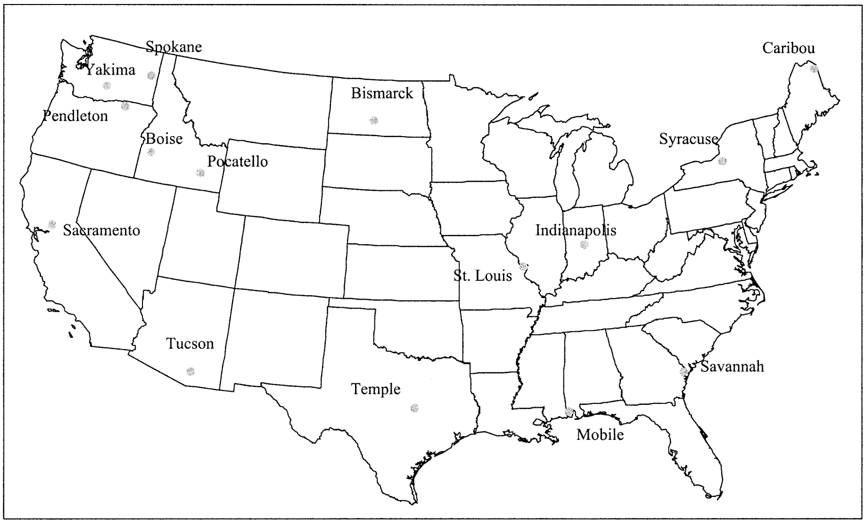


FIG. 1. Study sites with daily maximum and minimum temperature data for 1961–90.

was to evaluate the adequacy of generating temperature data from the normal distribution 1) by conducting a fundamental analysis of the assumption of normality in measured daily air temperature by testing the hypothesis that daily maximum and minimum temperature are normally distributed for each month and 2) by comparing synthetic temperature records generated with the normal distribution with measured temperature records.

2. Procedures

Daily maximum and minimum air temperature values for 15 sites (Fig. 1) for 1 January 1961–31 December 1990 were analyzed. For all of the sites except Temple, Texas, data were obtained from the National Oceanic and Atmospheric Administration Solar and Meteorological Surface Observation Network (SAMSON) databases. Temple data were obtained from the U.S. Department of Agriculture Agricultural Research Service (USDA-ARS) Grassland Soil and Water Research Laboratory.

First, graphical techniques were used to evaluate the normality of temperature data. Frequency histograms and probability plots for each site were graphed for January (winter), April (spring), July (summer), and October (autumn). An expected frequency curve (assuming a normal distribution with mean and standard deviation of the measured data) was placed on each histogram and probability plot to visually analyze goodness of fit and to determine if specific patterns were evident.

Quantitative evaluations were then used to identify possible deviations from the normal distribution. The Kolmogorov–Smirnov test ($\alpha = 0.05$) was used to evaluate the hypothesis that daily maximum and minimum temperatures are normally distributed in every month (Haan 1977). To provide another quantitative criterion, the coefficient of skew was calculated for each site for January, April, July, and October to supplement the evaluation of seasonal deviations from the normal distribution (Yevjevich 1972). The skew coefficient (ratio of the adjusted third moment to the cube of the standard deviation) has a value of 0 for the normal distribution (Brooks and Carruthers 1953; Haan 1977).

The mean and standard deviations of measured monthly data were used with the normal distribution to generate 30 yr of daily temperature data for each month. Generating temperature data with the measured mean and standard deviation ensures that generated monthly means and standard deviations are reproduced (in theory with sufficient sample size). However, it was important to compare generated and measured data because, whether or not measured temperatures were judged as normal in a strict statistical sense, 1) generated data may or may not adequately represent measured values, and 2) datasets generated from an infinite distribution, such as the normal distribution, may contain improbable extreme temperature values.

In order to compare measured and generated extreme events, the frequencies of measured and generated extreme hot days (values exceeding the monthly mean plus three standard deviations) and extreme cold days (values less than the monthly mean minus three standard deviations) were analyzed. This arbitrary classification of extreme hot and cold days was derived from the realization that 99.74% of data are within three standard deviations from the mean for normally distributed data (Haan 1977). This relative classification is preferred over an absolute threshold (such as extreme hot days have maximum temperatures greater than 38°C), which does not reflect normal local temperatures. The temperatures on the hottest and coldest days for each month over the 30-yr period were also analyzed.

Daily maximum and minimum temperatures have each been shown to be serially correlated and on the same day cross-correlated with other climate variables (Richardson 1982); however, the serial and cross correlation were neglected in this study to simplify the evaluation of normality. This simplification does not affect generation of monthly means and standard deviations but would affect analysis of time-dependent phenomena, such as hot spells and first freeze dates. To ensure values generated in this study were comparable to values generated with the normal distribution with associated correlation structure in place, data were compared with extreme values generated with CLIGEN and USCLIMATE for Bismarck, North Dakota; Caribou, Maine; Indianapolis, Indiana; Mobile, Alabama; and Tucson, Arizona, by Johnson et al. (1996).

3. Results and discussion

a. Graphical analysis

In comparing histograms plotted with expected normal frequency curves and normal probability plots for January (winter), April (spring), July (summer), and October (autumn), it appeared that for some months temperature data were adequately represented by the normal distribution (Fig. 2). However, for most months data appeared skewed and may not be adequately represented by the normal distribution (Figs. 3a,b). It also appeared that minimum temperature data generally fit the normal distribution more closely than maximum temperature data. In several locations such as Bismarck, measured data seemed to fit more of a rectangular distribution with numerous values about the mean but a sharp decline in measured frequencies at some distance from the mean (Fig. 4). These observations, made without regard to whether the normality hypothesis was accepted, were then confirmed quantitatively.

b. Analysis of normality

The Kolmogorov–Smirnov test was applied to a total of 180 months each for daily maximum and minimum temperature data (12 months for each of 15 sites). Significance levels (p values) for each test are given in Table 1. For both maximum and minimum temperature, tests indicated that the data were generally not normally distributed. For daily maximum temperature, the hypothesis that the data are normally distributed was rejected in 126 of 180 months; and for daily minimum temperature, the hypothesis was rejected in 119 of 180 months. The only readily apparent geographical pattern for normality in maximum temperature was that data from only 4 of 48 possible months were normally distributed for the four southernmost sites (Tucson; Savannah, Georgia; Temple; and Mobile). For minimum temperature, however, several geographic patterns were apparent. Minimum temperatures for April through October tended to be normally distributed in the northwestern sites, and for the winter months (November through January) they tended to be normal in the southwest. Minimum temperatures were not normally distributed in any month for Savannah; Mobile; St. Louis, Missouri; and Indianapolis.

During examination of the total number of months for which temperatures were considered normal by the Kolmogorov–Smirnov tests in Table 1, a distinct geographical pattern emerged for the continental United States (Fig. 5, Table 1). A noticeable gradient existed between sites in the southeastern United States, where virtually all months were nonnormal, and the north and west, where approximately one-half of all possible months (24 total) had normally distributed temperature data in the northern plains. This lends strong evidence to the concept that cold air outbreaks dropping southeastward from central Canada toward the southeast result in negatively skewed temperature distributions. This occasionally, but rather consistently, produces temperatures that are lower than might ‘‘normally’’ be expected. Across most of the northern and western sites, temperatures more often are normally distributed.

c. Analysis of skew

Skew coefficients, determined for each location for winter (January), spring (April), summer (July), and autumn (October), are shown in Table 2. Daily maximum and minimum air temperature tended to be skewed, thus indicating possible deviation from normality. Brooks and Carruthers (1953) indicated that if the magnitude of the skew coefficient does not exceed approximately 2 times the square root of 6 divided by the number of values (± 0.16 in this study), then doubt exists that the apparent skew is real. For the 15 sites, the magnitude of seasonal skew coefficients exceeded ± 0.16 in 70% of the cases for maximum temperature and in 80% of the cases for minimum temperature. Skew coefficients exhibited similar seasonal patterns for both minimum and maximum temperature (Figs. 6a,b). However, several noteworthy geographical patterns, which affected the patterns in normality noted in Fig. 5, were evident in skew for both minimum and maximum temperature.

For minimum temperature skew values in winter, a general north–south gradient existed across the country with slightly positive values in the southern sites and along the Atlantic coast, negative values in the midwestern sites, and strongly negative values in the northwest. Strongly negative skew values at the five inland northwest locations reflect occasional Arctic air masses that push into the region, producing extreme cold temperatures relative to typically mild, maritime conditions of the region (which are elevated in comparison with other continental locations at similar latitudes because of westerly flow off the Pacific Ocean). In the summer, sites in the midwestern and southeastern portions of the country had negatively skewed minimum temperatures, while minimum temperatures in Sacramento, California, exhibited strong positive skew. The strongly negative

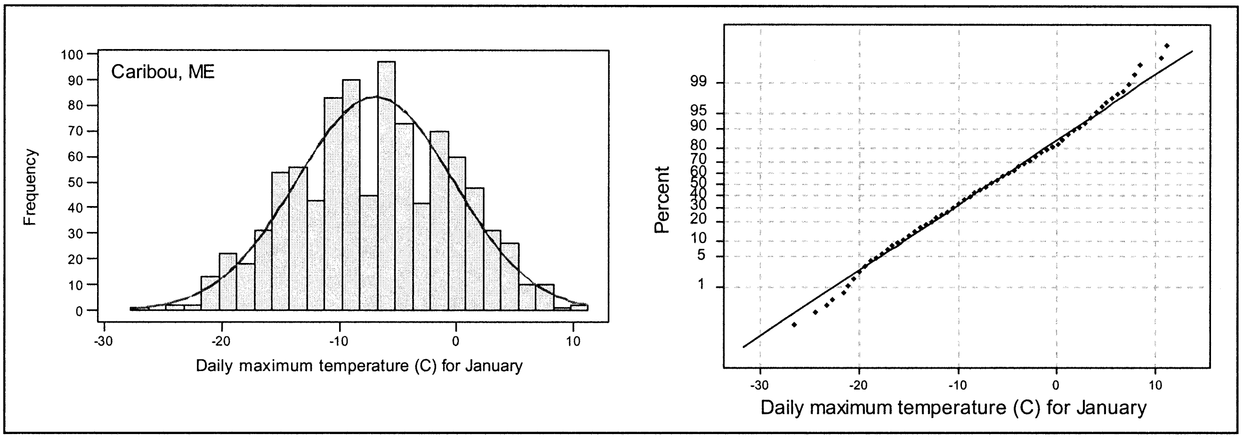
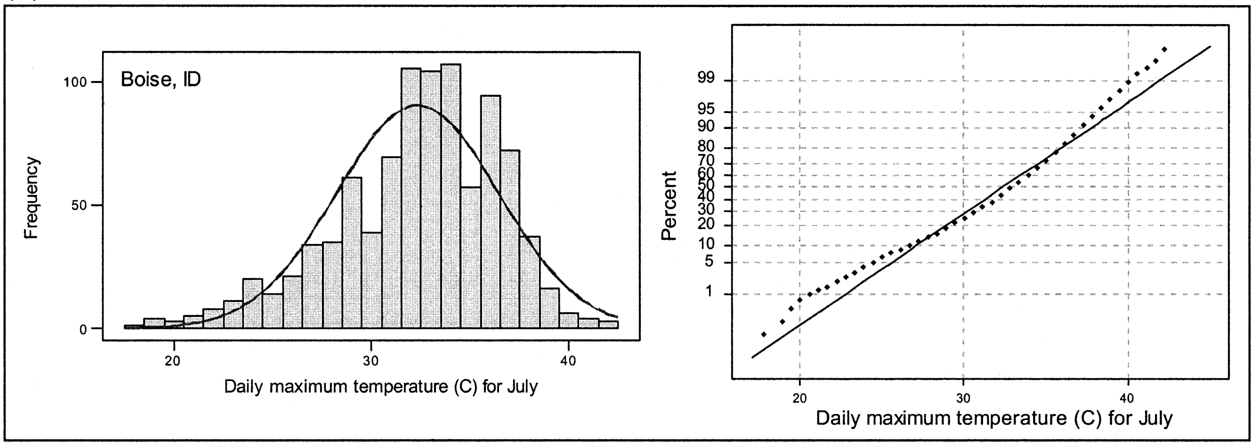


FIG. 2. Example of measured temperature data that appeared to be normally distributed.

(a)



(b)

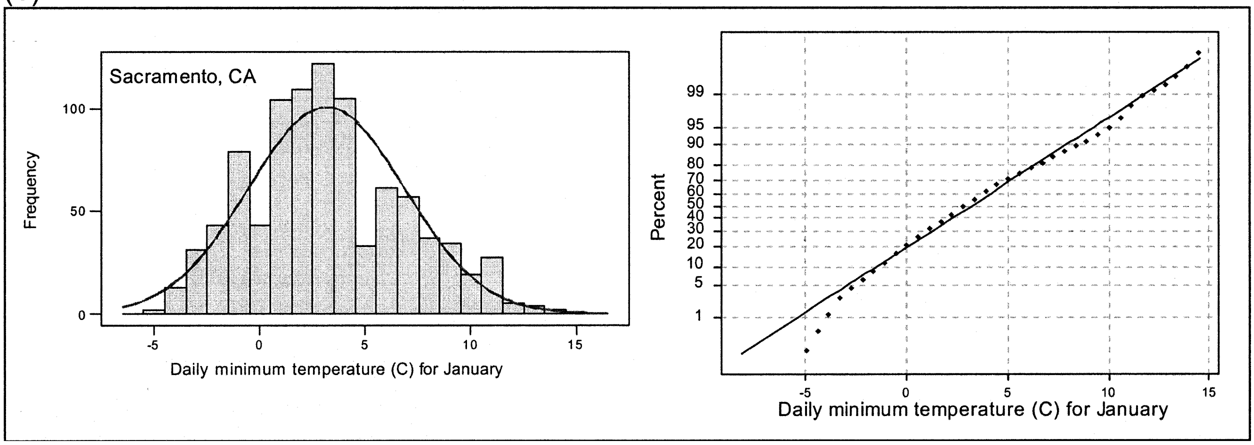


FIG. 3. Example of measured temperature data that appeared not to be normally distributed because of (a) negative skew and (b) positive skew.

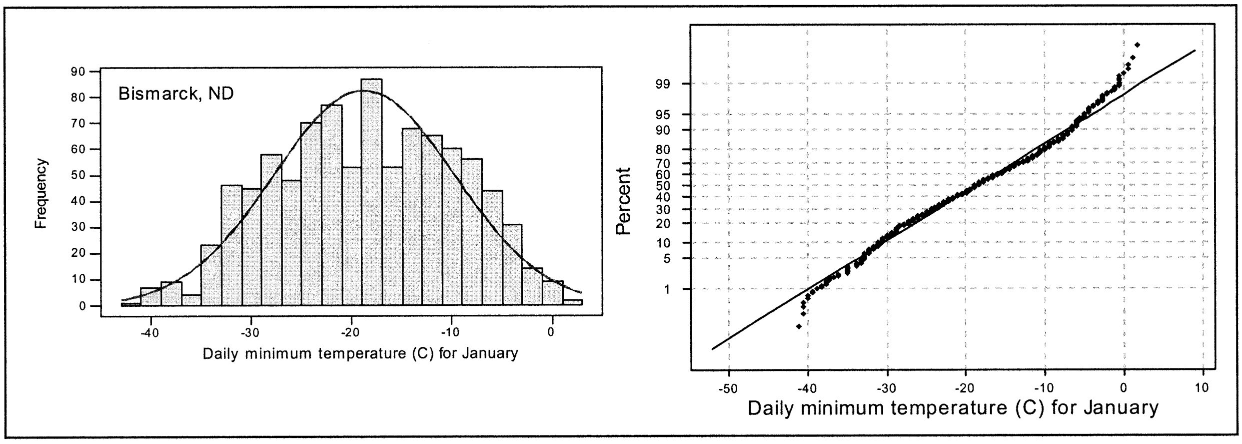


FIG. 4. Example of measured temperature data that appeared to fit a rectangular distribution.

skew values in the midwestern and southeastern sites can be largely attributed to occasional pushes of cooler and/or drier air behind cold fronts that produce much lower minimum temperatures than usually experienced in the warm, humid region. The skew value of +0.75 for Sacramento in July is most likely a relatively local effect due to occasional occurrences of the sea breeze failing to penetrate to Sacramento, which results in extremely warm nights as compared with average conditions in which inflows of cool, moist air from the San Francisco Bay move into the lower Sacramento Valley on summer evenings.

TABLE 1. Significance levels for the Kolmogorov–Smirnov test of normality. Boldface values represent p values greater than 0.05, therefore the hypothesis that data are normally distributed was not rejected.

Site	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	No. normal
						Minimum daily temperature*							
Bismarck, ND	0.000	0.000	0.000	0.000	0.039	**0.150**	**0.150**	**0.150**	**0.150**	**0.150**	0.000	0.000	5
Boise, ID	0.000	0.000	**0.150**	**0.083**	**0.150**	0.041	**0.150**	**0.150**	0.000	0.049	0.023	0.000	5
Caribou, ME	0.024	**0.150**	0.000	0.000	0.000	**0.150**	**0.150**	**0.074**	**0.124**	0.000	**0.101**	0.032	6
Indianapolis, IN	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.043	0.000	0.000	0
Mobile, AL	0.000	0.044	0.035	0.000	0.000	0.000	0.038	0.000	0.000	0.000	0.026	0.000	0
Pendleton, OR	0.000	0.000	0.040	**0.150**	**0.078**	**0.130**	0.035	**0.150**	**0.150**	**0.150**	0.000	0.000	6
Pocatello, ID	0.000	0.000	0.000	**0.058**	**0.150**	**0.150**	**0.150**	**0.150**	**0.150**	**0.150**	0.000	0.000	7
Sacramento, CA	0.000	**0.150**	0.000	0.000	0.032	0.047	**0.075**	**0.062**	**0.150**	**0.150**	0.000	0.000	5
Savannah, GA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0
Spokane, WA	0.000	0.000	0.000	0.018	**0.150**	**0.150**	**0.150**	**0.150**	0.034	**0.150**	0.000	0.000	5
St. Louis, MO	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.021	0.000	0.000	0
Syracuse, NY	0.000	**0.150**	**0.150**	**0.150**	0.000	0.000	0.000	0.000	0.024	**0.150**	**0.150**	**0.150**	6
Temple, TX	**0.078**	**0.150**	0.033	0.000	0.000	0.000	0.000	0.000	0.000	0.043	**0.083**	0.000	3
Tucson, AZ	**0.150**	**0.144**	**0.150**	**0.150**	0.034	**0.150**	**0.149**	**0.150**	0.000	0.000	0.025	**0.150**	8
Yakima, WA	0.000	0.000	0.000	0.014	0.027	**0.150**	**0.150**	**0.150**	**0.150**	**0.150**	0.000	0.000	5
						Maximum daily temperature							
Bismarck, ND	0.000	0.000	**0.150**	**0.057**	**0.150**	**0.150**	**0.150**	0.026	**0.150**	**0.150**	**0.150**	0.000	8
Boise, ID	0.000	0.000	**0.150**	0.000	**0.150**	**0.150**	0.000	0.000	0.000	**0.073**	**0.150**	0.000	5
Caribou, ME	**0.150**	**0.150**	0.000	0.000	0.036	**0.150**	0.000	**0.150**	0.000	0.014	0.000	**0.150**	5
Indianapolis, IN	**0.150**	**0.150**	0.000	**0.117**	0.023	0.000	**0.150**	0.036	0.000	0.000	0.000	0.000	4
Mobile, AL	0.000	0.000	0.000	0.000	**0.150**	**0.149**	0.000	0.000	0.000	0.000	0.000	0.000	2
Pendleton, OR	0.000	0.000	0.039	0.000	0.000	0.035	0.000	**0.136**	**0.104**	**0.150**	0.000	0.000	3
Pocatello, ID	0.000	0.022	**0.150**	0.000	0.045	**0.150**	0.000	0.000	0.000	0.000	**0.135**	0.000	3
Sacramento, CA	**0.150**	**0.150**	0.000	0.030	0.000	0.000	0.049	**0.150**	0.000	**0.150**	**0.150**	**0.150**	6
Savannah, GA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0
Spokane, QA	0.000	0.000	**0.069**	0.000	0.000	0.000	0.000	0.000	0.040	**0.150**	**0.088**	0.000	3
St. Louis, MO	**0.068**	0.000	0.000	**0.150**	0.000	0.000	**0.150**	**0.150**	0.043	0.000	0.000	0.037	4
Syracuse, NY	**0.150**	**0.150**	0.000	0.000	**0.117**	0.000	**0.150**	0.045	**0.150**	0.000	0.000	0.000	5
Temple, TX	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0
Tucson, AZ	**0.150**	0.000	0.000	0.000	0.000	0.048	0.027	**0.078**	0.000	0.000	0.000	0.000	2
Yakima, WA	**0.150**	0.000	0.000	0.000	0.000	0.020	0.000	**0.150**	**0.060**	**0.150**	0.000	0.041	4

* 0.000 represents < 0.01, 0.150 represents > 0.15.

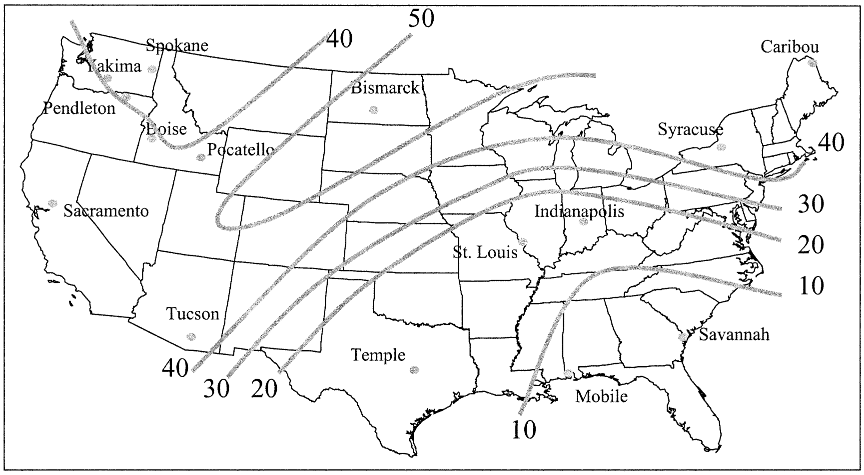


FIG. 5. Geographical distribution of the percentage of months with normally distributed daily minimum and maximum temperature (out of 24 possible months—12 each for minimum and maximum temperature).

Maximum temperature data for all of the southern sites were negatively skewed in all four seasons but especially strongly in the spring and autumn. These strongly negative skew values for the southern sites can be attributed to occasional invasions of cooler air from the north and to cloudy days with precipitation, both of which restrict temperatures from reaching their typical mean values closer to their maximum potential. Also noteworthy is the dominance of negative skew in maximum temperature in winter and summer (Figs. 6a,b). Skew values were fairly well distributed between positive and negative values in the other seasons for maximum temperature and in all seasons for minimum temperature.

d. Analysis of extremes

An examination of extreme cold and hot days was conducted by comparing the frequency of measured and generated extreme hot days (values exceeding the monthly mean plus three standard deviations) and extreme cold days (values less than the monthly mean minus three standard deviations). The temperature on the hottest and coldest days for each month over the 30-yr period were also compared for measured and generated records.

Generated extreme temperature data did match well with generated extreme values from CLIGEN and USCLIMATE for Bismarck, Caribou, Indianapolis, Mobile,

TABLE 2. Results of skew determinations for each season. Boldface values represent seasonal skew coefficients that exceed ±0.16, which for these datasets indicates ''real'' skew according to Brooks and Carruthers (1953).

Site	Daily minimum temperature				Daily maximum temperature			
	Jan	Apr	Jul	Oct	Jan	Apr	Jul	Oct
Bismarck, ND	−0.08	**−0.44**	**−0.19**	−0.08	**−0.18**	**0.23**	−0.06	−0.01
Boise, ID	**−0.68**	**0.17**	0.09	**−0.23**	**−0.50**	**0.48**	**−0.66**	0.03
Caribou, ME	**0.23**	**−0.54**	−0.03	**0.34**	−0.05	**0.45**	**−0.17**	**0.32**
Indianapolis, IN	**−0.39**	**0.26**	**−0.51**	0.11	−0.10	**−0.18**	−0.14	**−0.17**
Mobile, AL	0.15	**−0.27**	**−0.44**	−0.16	**−0.42**	**−0.73**	**−0.57**	**−0.53**
Pendleton, OR	**−1.07**	0.11	**0.25**	**−0.19**	**−0.52**	**0.56**	**−0.23**	0.15
Pocatello, ID	**−0.50**	**0.30**	−0.11	**0.21**	**−0.54**	**0.24**	**−0.86**	**−0.32**
Sacramento, CA	**0.36**	0.06	**0.75**	**−0.21**	−0.14	0.11	**−0.35**	0.04
Savannah, GA	**0.18**	**−0.33**	**−0.59**	**0.30**	**−0.18**	**−0.25**	−0.14	**−0.46**
Spokane, WA	**−0.84**	**0.34**	−0.06	**−0.17**	**−0.51**	**0.66**	**−0.38**	**0.19**
St. Louis, MO	**−0.25**	0.16	**−0.43**	0.15	0.08	−0.11	**−0.20**	−0.08
Syracuse, NY	**−0.27**	**0.49**	0.06	0.12	0.00	**0.32**	**−0.22**	0.07
Temple, TX	**0.19**	**−0.31**	**−0.51**	−0.12	**−0.29**	**−0.80**	**−0.71**	**−0.66**
Tucson, AZ	−0.13	0.03	**0.24**	**−0.46**	**−0.20**	**−0.57**	**−0.38**	**−0.77**
Yakima, WA	**−0.83**	**0.44**	0.01	0.04	−0.04	**0.50**	**−0.20**	0.04
Average	−0.26	0.03	−0.10	−0.06	−0.24	0.06	−0.35	−0.14
No. with +/− skew	5/10	10/5	6/9	6/9	2/13	9/6	0/15	7/8

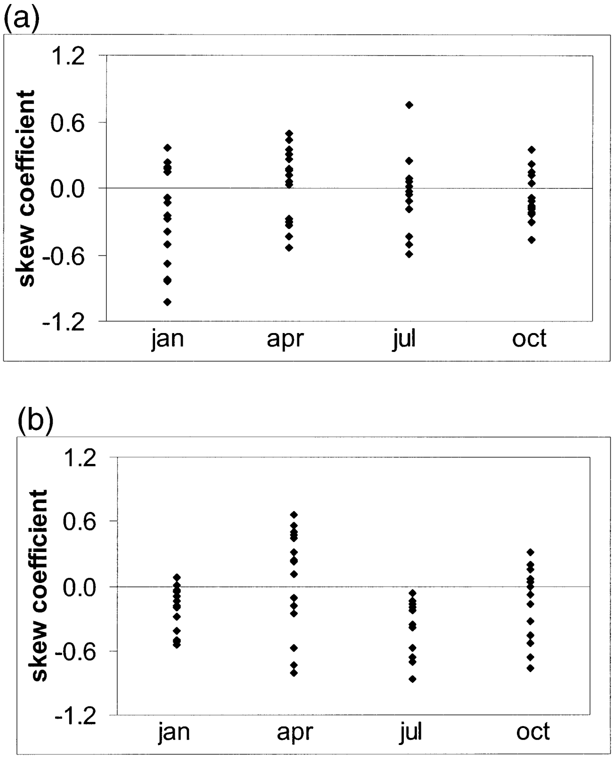


FIG. 6. Ranges of seasonal skew coefficients for (a) measured daily minimum temperature and (b) measured daily maximum temperature.

and Tucson, as reported by Johnson et al. (1996). Generated maximum temperature values were all within 4°C (mean difference 4%), and generated minimums were all within 8°C (mean difference 6%).

For extreme cold temperatures, differences between the frequency of generated and measured extreme cold days varied seasonally. Measured extreme cold days occurred much more often than were generated from November through March and to a lesser extent from June through September (Fig. 7). These differences can be attributed to measured extreme cold days at the five inland northwestern sites, such as Yakima, Washington, for November–March and to measured extreme cold summer days in the southern sites, such as Temple, for June–September.

For extreme hot temperatures, the frequency of generated extreme hot days exceeded the frequency of measured hot days throughout the year, but this difference was relatively small in comparison with minimum temperature (Fig. 8). For the southern locations, where large negative skew values existed in the historical maximum temperature record in all months, generated extreme hot days were, as expected, more frequent throughout the year. Greater differences across the rest of the country were noted from June through February.

The one-time hottest and coldest measured temperatures for each month over the 30-yr period were plotted against generated monthly maximums and minimums for each site. Generated extreme cold temperatures generally matched measured extremes, especially above −20°C (Fig. 9). However, it appeared that Arctic air masses that produce temperatures below −20°C are not adequately represented by a simple mean and standard deviation model such as the normal distribution. Figure 9 shows that little systematic error occurred in generated data (except below −20°C). Absolute errors for all months across the sites averaged 2.7°C. Coefficient of determination (R^2) values for generated and measured minimum monthly temperatures for each site ranged from 0.90 to 0.99 (with an overall R^2 = 0.93). The lowest R^2 values, below 0.93, were all from the five inland northwestern sites, which again can be attributed to a strong negative skews in minimum temperature. Thus for these sites from November to May, generating data with the normal distribution results in generated

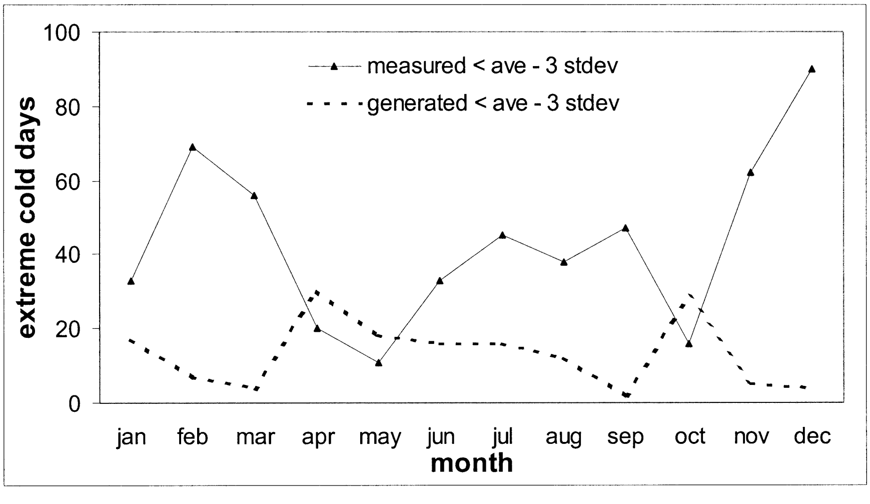


FIG. 7. Frequency of extreme cold daily minimum temperatures for measured and generated data (total for all 15 sites in a 30-yr period).

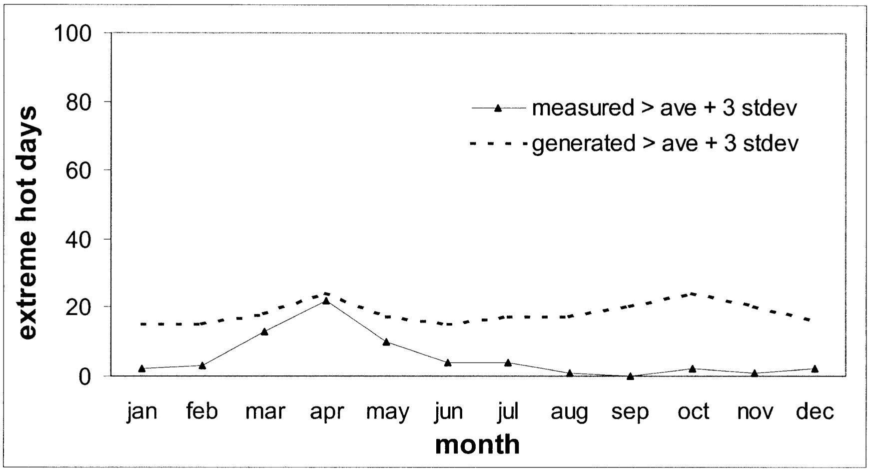


FIG. 8. Frequency of extreme hot daily maximum temperatures for measured and generated data (total for all 15 sites in a 30-yr period).

monthly extreme cold temperatures being warmer than measured extremes. A drastic example occurred in November for Spokane, Washington, when the coldest generated temperature was −16°C as compared with the measured extreme of −29°C.

Generated extreme hot temperatures did not match measured extremes as well as generated extreme cold temperatures (Fig. 10). Substantial systematic error is shown by Fig. 10, which shows that generated extreme hot temperatures exceeded measured extremes throughout the range of measured values. Only a few values of generated extreme hot temperatures were lower than

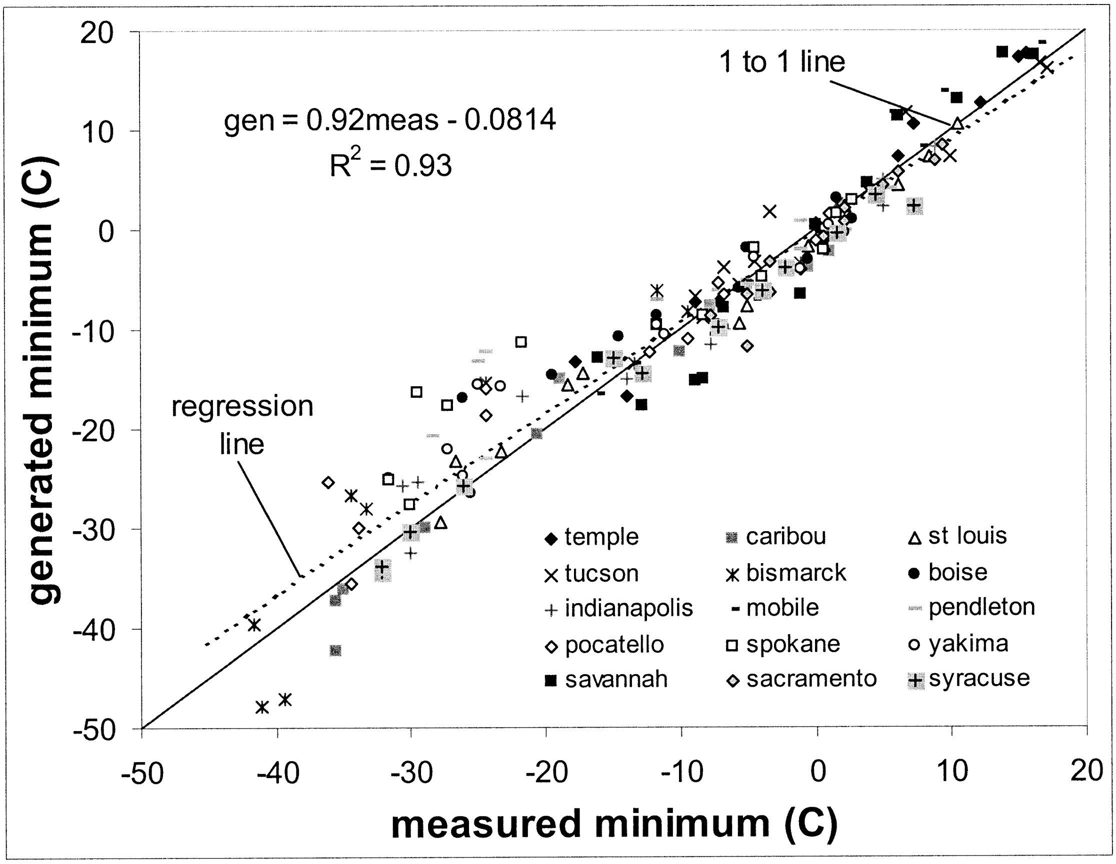


FIG. 9. Comparison of generated and measured extreme minimum temperatures for all months.

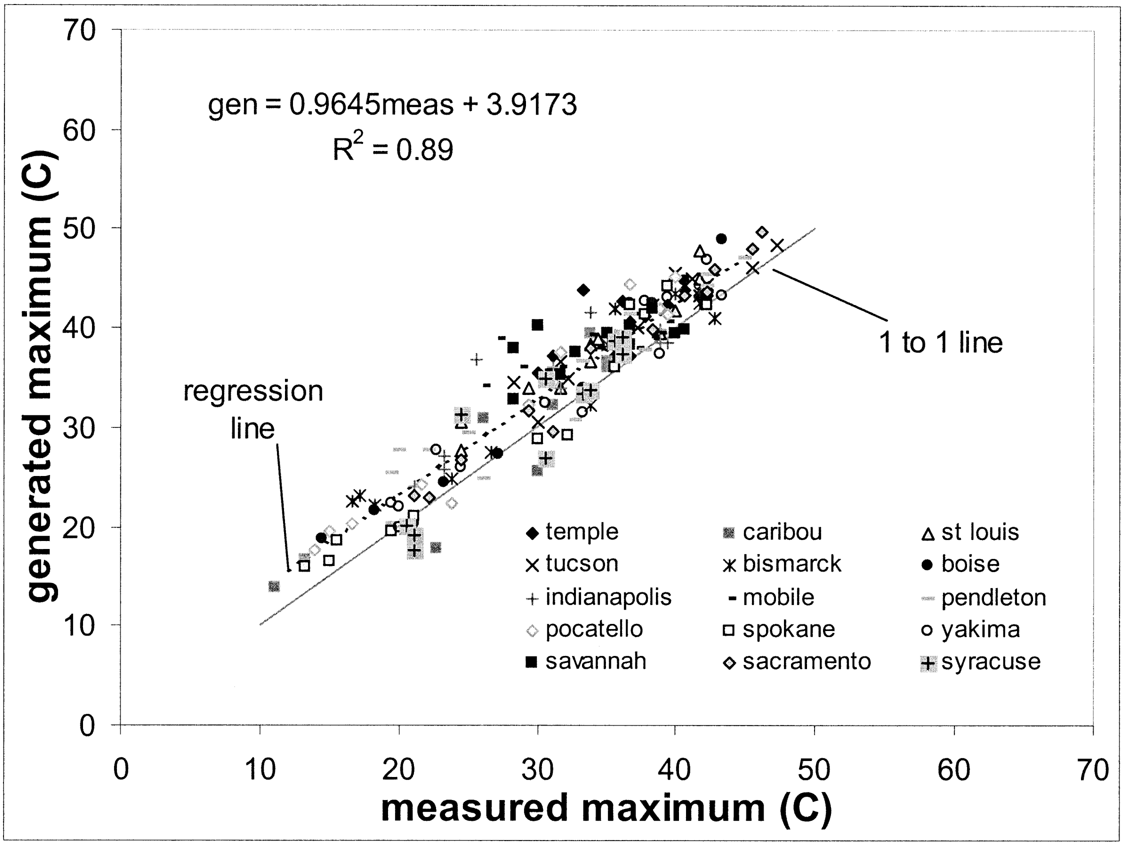


FIG. 10. Comparison of generated and measured extreme maximum temperatures for all months.

measured temperatures, and these generally occurred in the northeastern sites in the cooler months. Absolute errors for each month across the sites (average = 3.2°C) tended to be greater than those for extreme cold temperatures. The R^2 values for generated and measured maximum monthly temperatures ranged from 0.35 to 0.98 (with an overall $R^2 = 0.89$). The R^2 values for three southern sites, Savannah (0.35), Temple (0.47), and Mobile (0.57), were low in comparison with values for the other sites, which were all above 0.73. The difference is especially notable at these sites in colder months when generated extreme hot temperatures often greatly exceeded measured values (e.g., for Mobile in December, the generated extreme was 39°C as compared with a measured 27°C). At the northern and western sites, generated extreme hot temperatures exceeded measured values predominantly in the summer months. This most likely can be attributed to the common condition of near-maximum solar radiation creating temperatures near the physical bound of extreme hot temperature, especially at inland northwestern locations. The unbounded or infinite normal distribution, however, generates temperatures well above physically possible values.

4. Conclusions

The assumption of normality in measured temperature data and the adequacy of the normal distribution to model daily maximum and minimum temperature were examined in this study. The results indicate that measured daily maximum and minimum temperature are not generally normally distributed in each month but are indeed skewed. This finding contradicts a standard assumption in most weather generators that temperature data are normally distributed. This violation does not affect reproduction of monthly means and standard deviations but does result in simulated monthly temperature populations that do not represent the distribution of measured data. In addition, generating temperature from the unbounded normal distribution resulted in several physically improbable values (especially extreme hot temperatures). Thus, procedures to skew generated data and prevent generation of unrealistic temperature values need attention; however, the practical impact and use of alternative generation procedures in weather generator models deserves attention as well.

This study revealed substantial seasonal and geographic variability and regional patterns in temperature skew. The analysis of skew should be a useful guide for further study of temperature generation and should assist in providing a useful framework for the design of a weather generator capable of performing accurately in any part of the nation.

A continuation of this effort will examine other distributions and/or procedures to improve the temperature generation procedures in a weather generator under development, the Generation of Weather Elements for Multiple Applications (GEM) model. In contrast to this study, analysis of the temperature routine in the GEM model (which has the necessary serial and cross-correlation structure in place) will allow evaluation of properties such as frost-free period, length of cold and hot spells, first freeze, and so on. These important features, which impact climate change and crop simulation modeling, must be realistically represented by temperature routines in weather generators.

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